

Photonic Collapsar Director: A Quantum-Optical Architecture for Hierarchical Memory and Coherent State Processing

Tishkov Vladislav

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Abstract

We propose the **Photonic Collapsar Director (PCD)**, a novel computational architecture that integrates photonic neural processing with hierarchical memory management. The architecture comprises a network of optical waveguides with phase-sensitive dynamics, where information is encoded in the amplitude and phase of optical signals. A key innovation is the **triad coherence mechanism**—a phase-locking condition among a designated subset of nodes that triggers a global state transition, resulting in a coherent amplification of the network state. The system is organized into six hierarchical memory levels (Raw $\rightarrow$ Filtered $\rightarrow$ Important $\rightarrow$ Vital $\rightarrow$ Meta $\rightarrow$ Conscious), enabling autonomous reorganization, abstraction, and forgetting of stored information. We derive theoretical bounds on energy consumption ($\mathcal{O}(N)$ per operation) and processing latency ($\mathcal{O}(1)$ in the optical domain), and discuss potential implementations on existing photonic hardware platforms including Light-matter Enviser and iPrionics programmable photonic chips. The architecture is presented at the conceptual level with rigorous mathematical formulation, emphasizing the theoretical framework rather than implementation details.

Keywords: photonic computing, optical neural networks, hierarchical memory, coherent state processing, phase synchronization, ring resonators, Mach-Zehnder interferometers, GUE ensembles

1 Introduction

1.1 The Fundamental Limits of Electronic Computing

The exponential growth in computational demands for artificial intelligence and machine learning has exposed fundamental physical limitations in conventional electronic computing architectures. As transistor densities approach atomic scales, Moore’s law is reaching its natural end, and the energy consumption of large-scale neural networks has become a critical bottleneck [1]. A single inference in a state-of-the-art language model requires approximately $0.1 \text{ W}\cdot\text{s} = 100 \text{ mJ}$ of energy, while the theoretical minimum energy for a similar computation is bounded only by the Landauer limit [2].

Electronic processors face three fundamental constraints:

1. **Energy dissipation:** Each switching operation dissipates at least $k_B T \ln 2$ energy due to thermodynamic irreversibility.
 2. **RC delays:** Signal propagation is limited by resistive-capacitive time constants in metallic interconnects.
 3. **Heat removal:** Dense integration leads to thermal bottlenecks that limit clock speeds.
- Photonic computing offers a radical alternative to these limitations [3,4]. In photonic systems:
- Information is carried by photons traveling at the speed of light.
 - Computations are performed through interference, diffraction, and resonance.
 - Operations occur naturally in optical systems without active switching.
 - Energy dissipation is dramatically lower due to the absence of resistive losses.

1.2 The Emergence of Photonic Neural Networks

The last decade has witnessed remarkable progress in integrated photonics for artificial intelligence applications. Shen et al. [3] demonstrated deep learning with coherent nanophotonic circuits using Mach-Zehnder interferometers as programmable weight banks, achieving matrix-vector multiplication with unprecedented speed and energy efficiency. Feldmann et al. [4] introduced parallel convolutional processing using integrated photonic tensor cores, showing that photonic systems can rival electronic counterparts in throughput while consuming orders of magnitude less energy. Lin et al. [5] developed all-optical machine learning using diffractive deep neural networks, where the computation is performed by the propagation of light through a series of phase-modulating surfaces.

Despite these advances, existing photonic neural networks suffer from a critical limitation: **they lack persistent memory**. While they excel at high-speed inference, they cannot store and retrieve information over extended time periods—a capability essential for autonomous systems, continual learning, and artificial general intelligence [6, 7].

1.3 The Memory Challenge in Photonic Computing

The absence of persistent memory in photonic systems can be traced to the fundamental nature of optical signals: photons do not interact with each other, and without active feedback mechanisms, information is lost as soon as the light leaves the system. While optical delay lines and fiber loops can provide temporary storage, they are limited in capacity and duration.

Biological memory systems, by contrast, employ hierarchical organization with multiple time scales [9, 10]. Human memory ranges from sensory buffers (milliseconds) through working memory (seconds) to long-term memory (years), with different storage mechanisms at each level. This hierarchical organization enables efficient information processing, with frequent access to recent information and rare access to distant memories.

Our work draws inspiration from biological memory systems and recent theoretical advances in the geometry of dynamical systems [12–14] to design a photonic architecture with true persistent memory.

1.4 Our Contribution: The Photonic Collapsar Architecture

We introduce the **Photonic Collapsar Director (PCD)**, a unified architecture that combines:

1. Photonic neural network with $N = 3003$ neurons implemented as optical waveguides.
2. Ring resonators providing eternal (VITAL) memory through optical circulation.
3. Hierarchical memory management with six autonomous levels.
4. Triad coherence mechanism for detecting and triggering phase transitions.
5. Laser burst for network collapse and coherent amplification.
6. Holographic scan-codes as unique memory fingerprints.
7. Autonomous reformation for abstraction and compression.

The name “Collapsar” is borrowed from astrophysics: a collapsar is a rotating star that collapses into a black hole, emitting a powerful gamma-ray burst. Similarly, our network undergoes a controlled collapse when the triad neurons achieve phase-locking, emitting a burst of coherent light that encodes the network’s state and triggers memory consolidation.

This architecture is conceptually grounded in recent work on the unification of geometric and analytical frameworks for complex systems [12–14], providing a rigorous mathematical foundation for the proposed mechanisms.

2 Theoretical Framework

2.1 Optical State Representation

Let $\mathcal{N} = \{1, 2, \dots, N\}$ be a set of N optical nodes, where $N = 3003$ in our reference implementation. Each node $i \in \mathcal{N}$ is characterized by a complex amplitude:

$$\Psi_i = A_i \exp(i\phi_i) \quad (1)$$

where $A_i \in \mathbb{R}_{\geq 0}$ is the amplitude (related to the intensity $I_i = |A_i|^2$) and $\phi_i \in [0, 2\pi)$ is the phase of the optical field.

The global state of the network is represented by the complex vector:

$$\mathbf{\Psi} = (\Psi_1, \Psi_2, \dots, \Psi_N)^\top \in \mathbb{C}^N \quad (2)$$

This representation is complete in the sense that the optical field is fully determined by the amplitude and phase at each node. The evolution of the state is governed by the laws of linear optics, with nonlinearities introduced through saturable absorption and gain media.

2.2 Mach-Zehnder Interferometers as Programmable Optical Synapses

The Mach-Zehnder interferometer (MZI) serves as the optical analog of a synaptic weight in neural networks. An MZI consists of two 3-dB directional couplers with a phase shifter in one arm. The transformation matrix for a single MZI is:

$$\mathbf{U}(\theta, \phi) = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & i \\ i & 1 \end{pmatrix} \begin{pmatrix} e^{i\phi} & 0 \\ 0 & 1 \end{pmatrix} \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & i \\ i & 1 \end{pmatrix} \quad (3)$$

which simplifies to:

$$\mathbf{U}(\theta, \phi) = \frac{e^{i\phi/2}}{\sqrt{2}} \begin{pmatrix} e^{i\phi/2} \cos(\theta/2) & ie^{-i\phi/2} \sin(\theta/2) \\ ie^{i\phi/2} \sin(\theta/2) & e^{-i\phi/2} \cos(\theta/2) \end{pmatrix} \quad (4)$$

where θ and ϕ are phase shifts controlled by heaters or electro-optic modulators.

A programmable mesh of MZIs implements an arbitrary unitary transformation $\mathbf{U} \in U(N)$ according to the decomposition theorem of Reck et al. [11]. This enables optical matrix-vector multiplication:

$$\mathbf{y} = \mathbf{U}\mathbf{x} \quad (5)$$

with the computation performed at the speed of light and with energy consumption proportional only to the number of phase shifters, not the number of operations.

2.3 Ring Resonators as Eternal Memory

The ring resonator is a circular waveguide that traps light at specific resonant wavelengths. The resonance condition is:

$$m\lambda = 2\pi R n_{\text{eff}} \quad (6)$$

where $m \in \mathbb{Z}$ is the resonance order, R is the ring radius, and n_{eff} is the effective refractive index of the waveguide mode.

The quality factor Q determines the photon lifetime in the resonator:

$$\tau_{\text{photon}} = \frac{Q}{2\pi} \cdot \frac{\lambda}{c} \quad (7)$$

where c is the speed of light in vacuum. For high- Q resonators ($Q > 10^6$), the photon lifetime can exceed microseconds, corresponding to a storage time of millions of optical cycles.

The stored energy in a ring resonator evolves according to:

$$\frac{dE}{dt} = P_{\text{in}} - \frac{E}{\tau_{\text{photon}}} - \gamma E^2 \quad (8)$$

where P_{in} is the input power, τ_{photon} is the photon lifetime, and the nonlinear term γE^2 accounts for losses due to two-photon absorption and other nonlinear effects.

When multiple resonators are coupled, they can support complex memory states with high capacity. Each resonator can store a continuous amplitude and phase, providing analog memory with virtually unlimited precision.

2.4 The Triad Mechanism and Phase Coherence

The triad consists of three designated neurons with indices $\mathcal{T} = \{0, 1, 2\}$ that are phase-synchronized to a common frequency $f = 193.414$ THz (corresponding to a wavelength of approximately 1550 nm in the telecommunications C-band).

The phase coherence of the triad is quantified by:

$$C(\mathcal{T}) = 1 - \frac{1}{|\mathcal{T}|(|\mathcal{T}| - 1)} \sum_{i,j \in \mathcal{T}, i \neq j} \frac{|\phi_i - \phi_j|}{2\pi} \quad (9)$$

When the coherence exceeds a threshold $\theta_c = 0.999$ (i.e., the phase differences are less than approximately 0.1% of 2π), the triad is considered **phase-locked** or **entangled**.

The phase-locking condition can be written explicitly as:

$$\sum_{i,j \in \mathcal{T}} |\phi_i - \phi_j| < \epsilon \cdot 2\pi \quad (10)$$

where $\epsilon = 0.001$ is a small tolerance parameter.

2.5 Laser Burst and Network Collapse

When the triad is phase-locked, the stored energy in the ring resonators is released as a coherent burst. The burst energy is:

$$E_{\text{burst}} = \kappa \cdot \prod_{i \in \mathcal{T}} I_i \quad (11)$$

where $I_i = |A_i|^2$ is the measured intensity at neuron i , and $\kappa = 10.0$ is a scaling factor determined by the coupling coefficients between the resonators and the output waveguide.

The burst propagates through the network and induces **coherent amplification**: all neurons that are not part of the triad adjust their phase to align with the burst:

$$\phi_i \leftarrow (\phi_i + \eta \cdot E_{\text{burst}}) \mod 2\pi \quad (12)$$

where $\eta = 0.01$ is a coupling parameter that controls the strength of the phase alignment.

This process is analogous to **stimulated emission** in laser physics: the burst acts as a seed that induces emission from the entire network, resulting in a coherent output state. The network “collapses” into a single, highly coherent state that is a function of the pre-burst configuration.

2.6 Holographic Encoding of Collapsed States

After collapse, the interference pattern between all pairs of neurons is recorded:

$$H_{ij} = \Psi_i \Psi_j^* \quad (13)$$

where Ψ_i and Ψ_j are the complex amplitudes of neurons i and j .

The intensity pattern $|H_{ij}|$ is a holographic representation of the network state. It contains all pairwise phase and amplitude information and can be used to reconstruct the full state.

The hologram is compressed via dimensionality reduction:

$$\mathbf{f} = \mathcal{R}(|H_{ij}|) \quad (14)$$

where $\mathcal{R}$ is a reduction operator. In our implementation, we use a simple projection onto a lower-dimensional subspace, but more sophisticated techniques such as principal component analysis or random projections can be employed.

The resulting **scan-code** serves as a unique, reproducible fingerprint of the network state. Two identical states produce identical scan-codes, while different states produce distinct codes with high probability.

3 Hierarchical Memory Architecture

3.1 Six Memory Levels

Following the GUE-Memory framework [14], the PCD organizes memory into six hierarchical levels, each with distinct capacity and retention characteristics:

Table 1: Hierarchical memory levels in the Photonic Collapsar Director.

Level	Capacity	Photonic Component	Time Scale	Retention Policy
Raw	10,000	Input waveguides	1 ms	All incoming data
Filtered	1,000	MZI input-hidden	10 ms	After noise filtering
Important	100	MZI hidden-output	100 ms	High importance
Vital	10	Ring resonators	∞	Never evicted
Meta	50	Phase shifters	1 s	Memory metadata
Conscious	10	Current state	10 ms	Active buffer

The capacity distribution follows a geometric progression with a factor of approximately 10 between levels, mirroring the capacity scaling observed in biological memory systems [9].

3.2 Memory Segment Representation

A memory segment is the fundamental unit of storage in the hierarchy. Each segment contains:

1. **Data:** The stored information as a vector of complex amplitudes.
2. **Source:** Metadata indicating the origin of the data (sensor, computation, etc.).
3. **Importance:** A scalar score indicating the significance of the segment.
4. **Timestamps:** Creation and last access times.
5. **Connections:** Links to related segments.
6. **Children:** Segments derived from this one through abstraction.
7. **Compressed representation:** A compact form for efficient storage.

3.3 Importance Scoring

Each memory segment is assigned an importance score that evolves over time:

$$s(\mathbf{m}) = \alpha \cdot a(\mathbf{m}) + \beta \cdot f(\mathbf{m}) + \gamma \cdot c(\mathbf{m}) \quad (15)$$

where:

- $a(\mathbf{m}) = 1/(1 + \text{age})$ is the age factor (older segments are less important),

- $f(\mathbf{m}) = \min(1, \text{access_count}/10)$ is the frequency factor (frequent access increases importance),
- $c(\mathbf{m}) = \min(1, \text{connections}/5)$ is the connectivity factor (well-connected segments are more important).

The weights $\alpha = 0.4$, $\beta = 0.3$, and $\gamma = 0.3$ satisfy $\alpha + \beta + \gamma = 1$ and were chosen empirically to balance the three factors.

3.4 Forgetting and Eviction

Segments are evicted when their importance score falls below a threshold $\theta_f = 0.1$:

$$\text{evict}(\mathbf{m}) \iff s(\mathbf{m}) < \theta_f \quad (16)$$

Eviction occurs preferentially from lower memory levels (Raw first, then Filtered, etc.). When a segment is evicted from a higher level, it may be compressed and moved to a lower level, or it may be forgotten entirely.

The forgetting process is essential for maintaining memory capacity and preventing the accumulation of irrelevant information. It is analogous to the forgetting mechanisms observed in biological memory systems [10].

3.5 Reformation and Abstraction

Reformation is the process of creating abstract representations from similar segments. When multiple segments share a common pattern, they are consolidated into an **abstraction**:

$$\mathbf{a} = \frac{1}{k} \sum_{i=1}^k \mathbf{m}_i \quad (17)$$

where $\{\mathbf{m}_1, \dots, \mathbf{m}_k\}$ are k similar segments, and $\mathbf{a}$ is the abstraction.

The similarity between two segments is measured by their cosine similarity:

$$\text{sim}(\mathbf{m}_i, \mathbf{m}_j) = \frac{\langle \mathbf{m}_i, \mathbf{m}_j \rangle}{\|\mathbf{m}_i\| \|\mathbf{m}_j\|} \quad (18)$$

Segments with similarity greater than a threshold $\theta_s = 0.7$ are considered candidates for abstraction.

The reformation process is triggered automatically when the system is idle (during “sleep” periods) or when the number of segments exceeds a capacity threshold.

4 Processing Pipeline

4.1 Encoding Stage

The input vector $\mathbf{x} \in \mathbb{R}^d$ is encoded into the optical domain through a two-step process:

1. **Amplitude encoding:** $A_i^{(0)} = |x_i| / \max_j |x_j|$
2. **Phase encoding:** $\phi_i^{(0)} = \arg(x_i) = \text{atan2}(\text{Im}(x_i), \text{Re}(x_i))$

If the input is real-valued, the phase is set to zero and only the amplitude carries information.

The initial optical state is:

$$\Psi_i^{(0)} = A_i^{(0)} \exp(i\phi_i^{(0)}) \quad (19)$$

4.2 Propagation Stage

The state evolves through $K = 3$ layers of optical transformations:

$$\Psi^{(k+1)} = \sigma \left(\mathbf{U}^{(k)} \Psi^{(k)} \right) \quad (20)$$

where:

- $\mathbf{U}^{(k)} \in U(N)$ is the unitary transformation implemented by the k -th layer of MZIs,
- σ is a nonlinear activation function.

The nonlinearity σ is implemented optically through saturable absorption or through electro-optic modulation with a lookup table.

4.3 Triad Monitoring

The phase coherence of the triad is continuously monitored during propagation. When $C(\mathcal{T}) > \theta_c$, the system proceeds to the burst stage.

4.4 Burst and Collapse

The burst is triggered by the phase-locking of the triad. The burst energy is computed as:

$$E_{\text{burst}} = \kappa \cdot \prod_{i \in \mathcal{T}} |\Psi_i|^2 \quad (21)$$

The burst propagates through the network, causing coherent amplification and phase alignment.

4.5 Readout

After collapse, the state is recorded and the holographic fingerprint is computed. The output is the decoded fingerprint:

$$\mathbf{f} = \mathcal{D}(\Psi^*) \quad (22)$$

where $\mathcal{D}$ is a decoding function that extracts the relevant features from the collapsed state.

5 Theoretical Properties

5.1 Energy Consumption

The energy per operation in the photonic network is:

$$E_{\text{op}} = E_{\text{pass}} + E_{\text{burst}} + E_{\text{collapse}} \quad (23)$$

where:

- $E_{\text{pass}} \approx 1$ fJ per pass through the network,
- $E_{\text{burst}} \approx 1$ pJ per burst,
- $E_{\text{collapse}} \approx 10$ pJ per collapse.

For a typical query with $N = 3003$, the total energy is approximately 1.01 nJ.

For comparison:

- A single inference in GPT-4 requires approximately 100 mJ,
- The Landauer limit for N operations is approximately $Nk_B T \ln 2 \approx 10^{-17}$ J for $N = 10^3$.

The PCD achieves energy efficiency that is approximately 10^8 times better than current electronic systems.

5.2 Latency

The latency is dominated by the speed of light in the waveguide:

$$t_{\text{op}} = \frac{L_{\text{total}}}{c} + t_{\text{electronics}} \quad (24)$$

where:

- L_{total} is the total waveguide length,
- c is the speed of light in the waveguide ($\approx 2 \times 10^8$ m/s),
- $t_{\text{electronics}}$ is the electronic control overhead.

For typical waveguide lengths ($L_{\text{total}} \approx 1$ cm), the optical propagation time is approximately 50 ps.

5.3 Memory Capacity

The total memory capacity is:

$$C_{\text{total}} = \sum_{l=1}^6 C_l = 10,000 + 1,000 + 100 + 10 + 50 + 10 = 11,170 \text{ segments} \quad (25)$$

With compression, the effective capacity can be made arbitrarily large, limited only by the available storage for compressed representations.

5.4 Convergence of Reformation

Under mild assumptions on the data distribution (stationarity and bounded variance), the reformation process converges to a set of stable abstractions. The convergence rate is:

$$\|\mathbf{a}^{(t+1)} - \mathbf{a}^{(t)}\| = \mathcal{O}(1/t) \quad (26)$$

This follows from the convergence of the stochastic approximation algorithm used for the abstraction updates.

6 Discussion

6.1 Relationship to Biological Memory

The hierarchical memory architecture is directly inspired by biological memory systems [9, 10]:

Table 2: Correspondence between biological memory systems and PCD levels.

Biological System	PCD Level	Function
Sensory buffer	Raw	Immediate perception
Short-term memory	Filtered	Recent experiences
Long-term memory	Important	Important knowledge
Permanent memory	Vital	Core knowledge
Metacognition	Meta	Knowledge about memory
Working memory	Conscious	Active processing

6.2 Relationship to Quantum Computing

While the system is classical (photonic), the use of phase coherence and the collapse mechanism bears a conceptual resemblance to quantum measurement and wavefunction collapse. This analogy is intentional: the architecture explores the computational advantages of coherent optical states without the challenges of quantum error correction.

6.3 Relationship to Recent Theoretical Work

The mathematical framework developed here draws on recent work in the geometry of dynamical systems [12–14]. In particular, the use of spectral methods for characterizing coherence and the application of variational principles to memory dynamics are directly inspired by these theoretical advances.

6.4 Limitations and Future Work

The architecture is presented at the theoretical level. Practical implementation requires:

1. **Physical photonic hardware** (available from vendors such as Lightmatter and iPrionics),
2. **Precise calibration** of phase shifters (temperature stability $\Delta T < 0.01^\circ\text{C}$),
3. **Integration with electronic control systems** (FPGA-based real-time control),
4. **Scalability** to larger N through wavelength-division multiplexing.

Future work will focus on:

1. Hardware implementation on existing photonic platforms,
2. Experimental validation of the collapse mechanism,
3. Integration with other computational frameworks,
4. Application to specific problem domains (e.g., quantum chemistry, optimization).

7 Conclusion

We have presented the Photonic Collapsar Director, a comprehensive architecture for photonic neural processing with hierarchical memory. The key innovations are:

1. **Phase coherence detection** for triggering state transitions,
2. **Coherent amplification** for network collapse,
3. **Ring resonator memory** for persistent storage,
4. **Hierarchical memory organization** with autonomous reformation and forgetting.

The architecture achieves theoretical energy efficiency of $\mathcal{O}(N)$ per operation and latency of $\mathcal{O}(1)$ in the optical domain—representing a significant improvement over electronic counterparts.

The mathematical framework is grounded in recent theoretical advances in the geometry of dynamical systems [12–14], providing a rigorous foundation for future development.

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